Embedded Bayesian Perception and Collision Risk Assessment (invited talk)

Christian Laugier

Embedded Bayesian Perception and Collision Risk Assessment

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ADAS & Autonomous Driving

Invited Talk
IEEE ICRA 2017 Workshop on Robotics and Vehicular Technologies for Self-driving cars
Sands Expo and Convention Center, Marina Bay Sands, Singapore June 2nd 2017

Autonomous Cars & Driverless Vehicles

- Strong involvement of Car Industry & Large media coverage
- An expected market of 500 B€ in 2035
- Technologies Validation => Numerous recent & on-going real-life experiments (in addition to simulation & formal methods)

Tesla Autopilot based on Radar & Mobileye

3D Lidar & Dense 3D mapping
Numerous vehicles & miles covered

Mobility Service

Cybus experiment, La Rochelle 2012
=> *CityMobil Project & Inria*

Drive Me trials
- *100 Test Vehicles in Göteborg, 80 km, 70km/h*
- *No pedestrians & Plenty of separations between lanes*

Robot Taxi testing in Pittsburgh *(Uber)* & Singapore *(nuTonomy)*
+ Google / Lyft ?
*=> **Mobility Service**, Numerous Sensors … Engineer in the car during testing*

Several benign & serious accidents in past few, numerousmilmonths (Tesla, Google, Uber…)

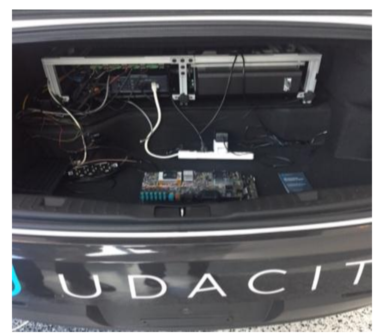
Safety is still not guaranteed !

Perception: State of the Art & Today's Limitations

- Despite significant improvements during the last decade of both Sensors & Algorithms, **Embedded Perception** is still one of the major bottleneck for Motion Autonomy

  => Obstacles detection & classification errors, incomplete processing of mobile obstacles, collision risk weakly address, scene understanding partly solved…

- **Lack of Robustness & Efficiency & Embedded integration** is still a significant obstacle to a full deployment of these technologies



Lack of Robustness & Efficiency

Lack of Integration into Embedded Sw/Hw

Trunk most of the time full of electronics & computers & processor units
=> High computational capabilities are still required

Focus of the talk

Complex Dynamic Scenes understanding

Situation Awareness & Decision-making

Dealing with unexpected events
e.g. Road Safety Campaign, France 2014

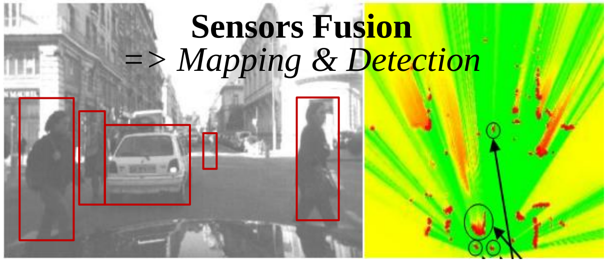
Anticipation & Prediction
for avoiding upcoming accidents

Main features

- ✓ Dynamic & Open Environments => *Real-time processing*
- ✓ Incompleteness & Uncertainty => *Appropriate Model & Algorithms (probabilistic approaches)*
- ✓ Sensors limitations => *Multi-Sensors Fusion*
- ✓ Human in the loop => *Interaction & Behaviors & Social Constraints (including traffic rules)*
- ✓ Hardware / Software integration => *Satisfying Embedded constraints*

Key Technology 1: Embedded Bayesian Perception

Embedded Multi-Sensors Perception
⇒ Continuous monitoring of the dynamic environment



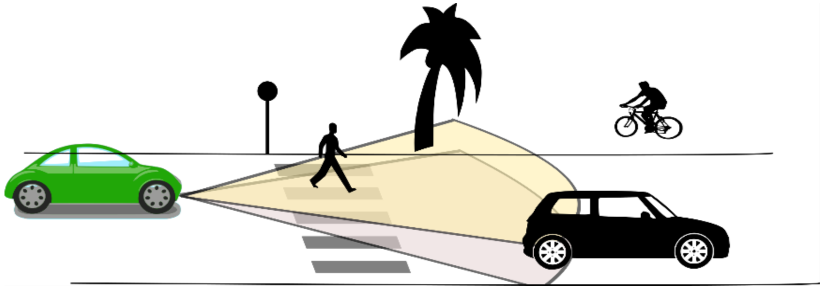
❑ Main challenges

- ✓ *Noisy data, Incompleteness, Dynamicity, Discrete measurements*
- ✓ ***Strong Embedded & Real time constraints***

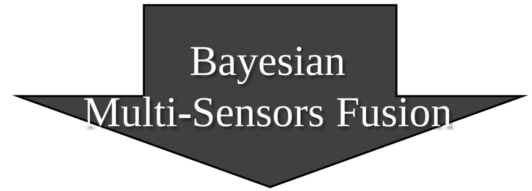
❑ Approach: Embedded Bayesian Perception

- ✓ *Reasoning about **Uncertainty & Time window** (Past & Future events)*
- ✓ ***Improving robustness** using **Bayesian Sensors Fusion***
- ✓ ***Interpreting the dynamic scene** using **Contextual & Semantic** information*
- ✓ ***Software & Hardware integration** using GPU, Multicore, Microcontrollers…*

Bayesian Perception : Basic idea

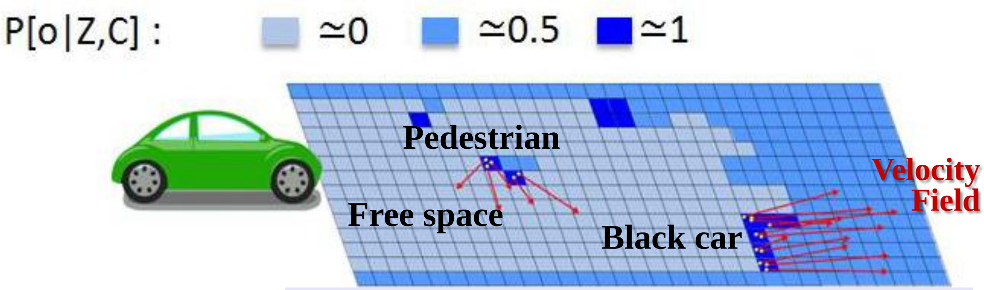


- Multi-Sensors Observations
  Lidar, Radar, Stereo camera, IMU …



Real-time

- Probabilistic Environment Model
  - ✓ *Sensor Fusion*
  - ✓ *Occupancy grid integrating uncertainty*
  - ✓ *Probabilistic representation of Velocities*
  - ✓ *Prediction models*



Concept of Dynamic Probabilistic Grid
⇒Occupancy & Velocity probabilities
⇒Embedded models for Motion Prediction

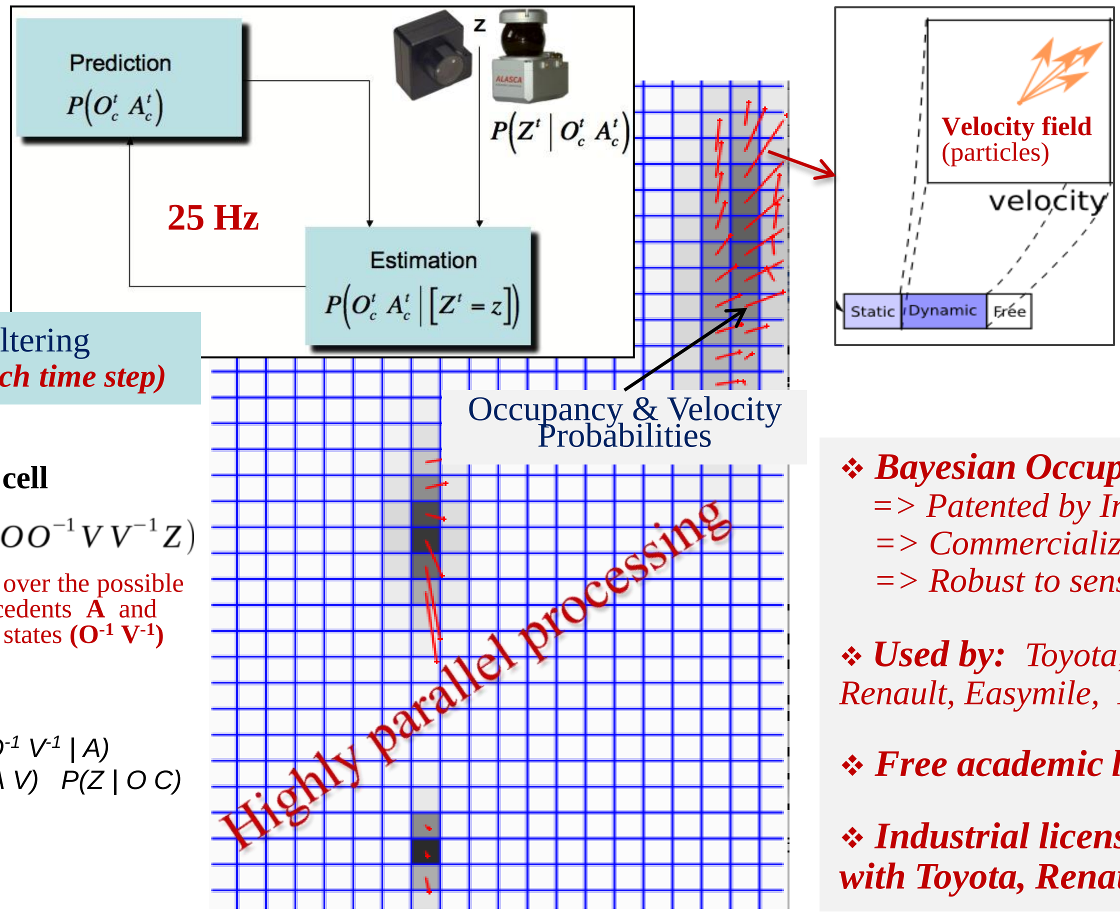
- Main philosophy
  Reasoning at the grid level as far as possible for both :
  - ***Improving efficiency*** *(highly parallel processing)*
  - ***Avoiding traditional object level processing problems*** *(e.g. detection errors, wrong data association…)*

A new framework: Dynamic Probabilistic Grids

=> *A clear distinction between Static & Dynamic & Free components*

[Coué & Laugier IJRR 05] [Laugier et al ITSM 2011] [Laugier, Vasquez, Martinelli Mooc uTOP 2015]

Sensing *(Observations)*



Bayesian Filtering
(Grid update at each time step)

Solving for each cell

$$P(O\,V \mid Z\,C) = \lambda \sum_{A\,O^{-1}V^{-1}} P(C\,A\,O\,O^{-1}\,V\,V^{-1}\,Z)$$

Sum over the possible antecedents **A** and their states **(O^{-1} V^{-1})**

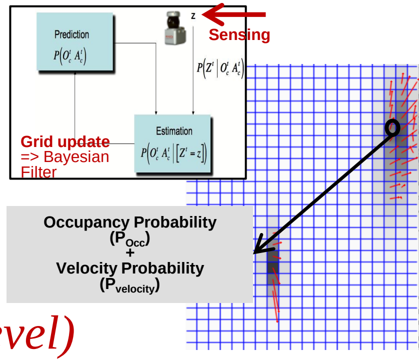
Joint Probability decomposition:

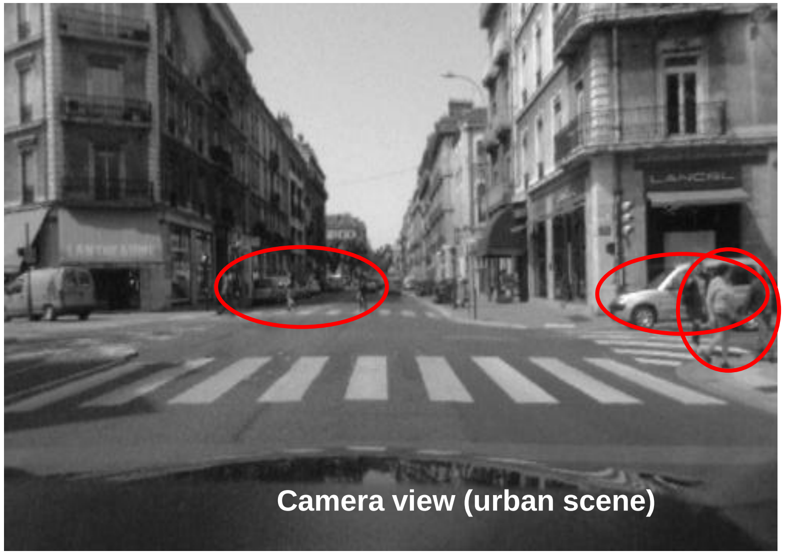
$$P(C\ A\ O\ O^{-1}\ V\ V^{-1}\ Z) = P(A)\ \ P(O^{-1}\ V^{-1} \mid A)\ \ P(O\ V \mid O^{-1}\ V^{-1})\ \ P(C \mid A\ V)\ \ P(Z \mid O\ C)$$

- ***Bayesian Occupancy Filter (BOF)***
  => Patented by Inria & Probayes
  => Commercialized by Probayes
  => Robust to sensing errors & occultation
- ***Used by:*** *Toyota, Denso, Probayes, Renault, Easymile, IRT Nanoelec / CEA*
- ***Free academic license available***
- ***Industrial license under negotiation with Toyota, Renault, Easymile***

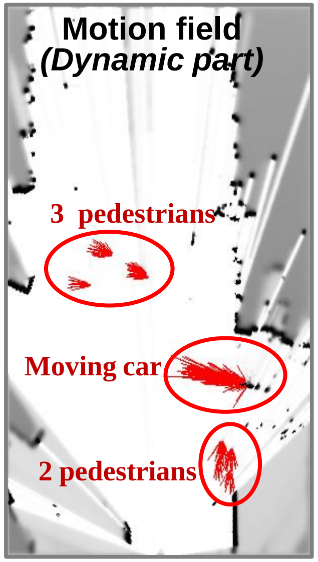
Bayesian Occupancy Filter (BOF) – *Main Features*

- Estimate **Spatial occupancy for each cell of the grid** ***P (O | Z)***
- **Grid update** is performed in <u>each cell in parallel</u> *(using BOF equations)*
- **Extract Motion Field** *(using Bayesian filtering & Fused Sensor data)*
- **Reason at the Grid level** *(i.e. no object segmentation at this reasoning level)*





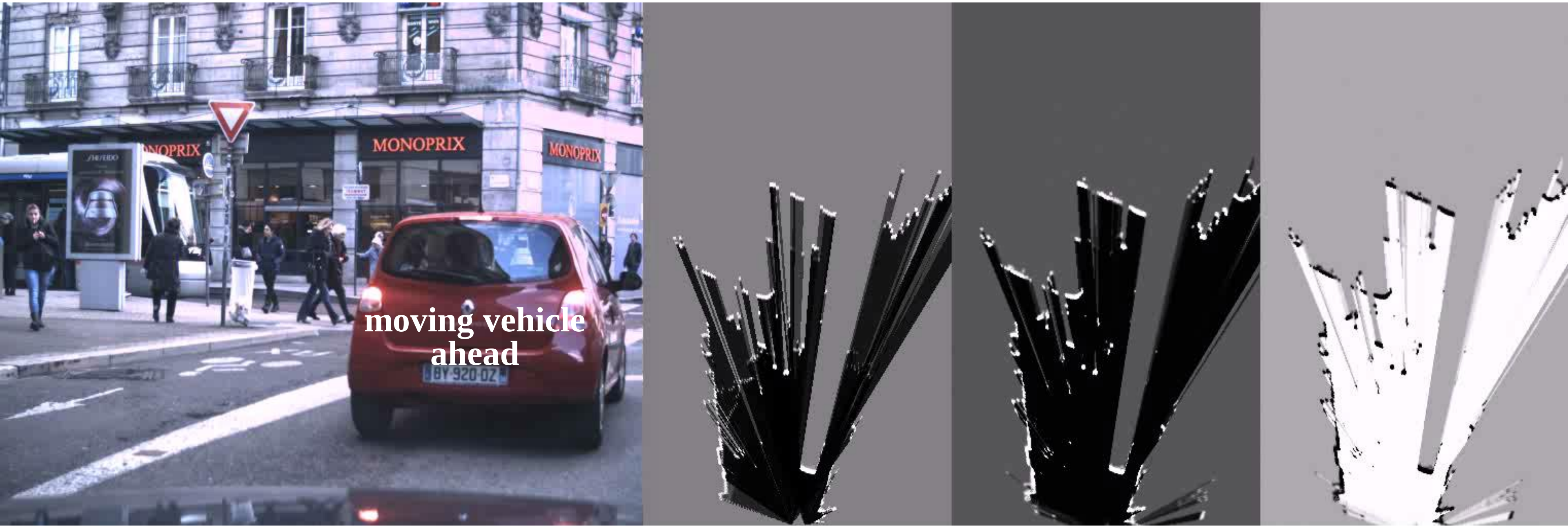
Sensors data fusion
+
Bayesian Filtering



Exploiting the Dynamic information for improving Scene Understanding !!

Experimental Results in dense Urban Environments

Observed Urban Traffic scene

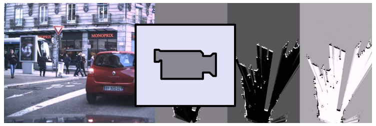


Ego Vehicle *(not visible on the video)*

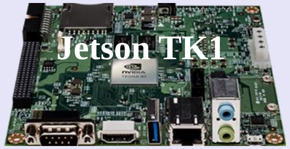
OG Left Lidar

OG Right Lidar

OG Fusion
+
Velocity Fields



Recent implementations & Improvements



*Several implementations (models & algorithms) more and more adapted to **Embedded constraints & Scene complexity***

❖ Hybrid Sampling Bayesian Occupancy Filter (HSBOF, 2014) *[Negre et al 14] [Rummelhard et al 14]*

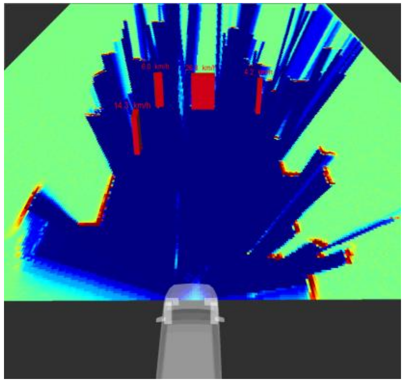
*=> Drastic **memory size reduction** (factor 100) + Increased **efficiency** (complex scenes)*
*+ More **accurate Velocity estimation** (using Particles & Motion data from ego-vehicle)*

❖ Conditional Monte-Carlo Dense Occupancy Tracker (CMCDOT, 2015) *[Rummelhard et al 15]*

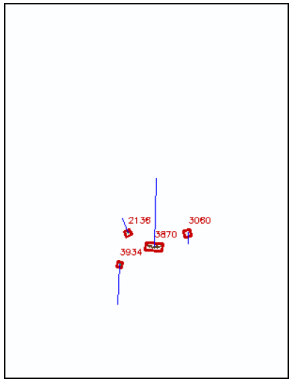
***=> Increased efficiency using** "state data" (Static, Dynamic, Empty, **Unknown**) + Integration of a **"Dense Occupancy Tracker"** (Object level, Using particles propagation & ID)*

❖ CMCDOT + Ground Estimator (under Patenting, 2017) *[Rummelhard et al 17]*

=> Ground shape estimation & Improve obstacle detection (avoid false detections on the ground)



Grid & Pseudo-objects



Tracked Objects

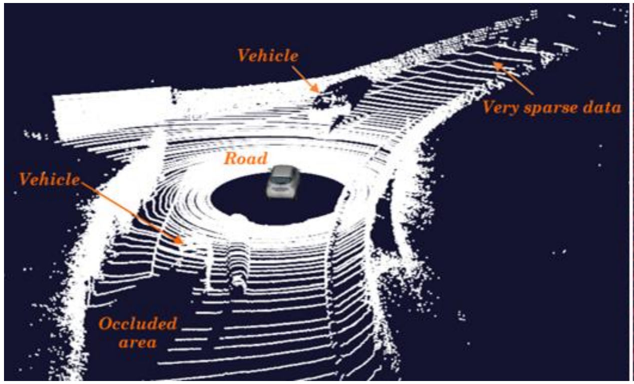
Classification *(using Deep Learning)*

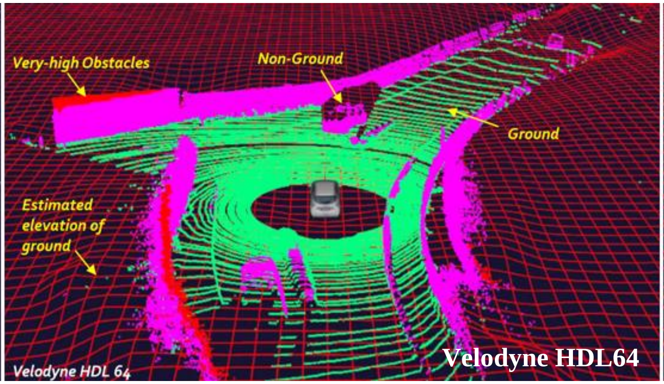
Detection & Tracking & Classification

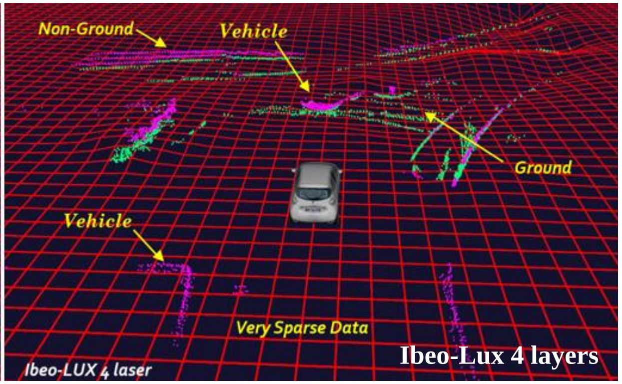
Ground Estimation & Point Cloud Classification

⇒ *Smart OG generation taking into account the **ground shape** & **height of laser impacts***

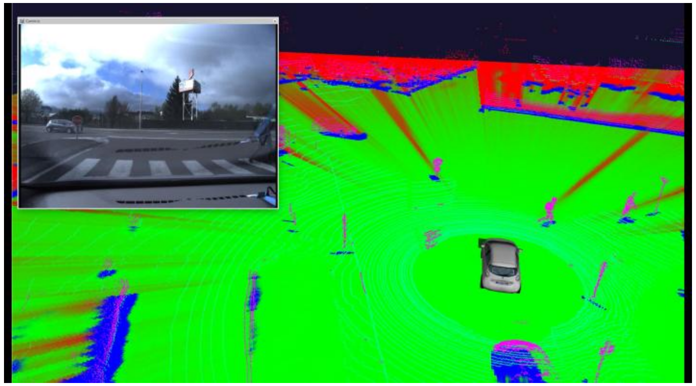
⇒ *Process properly sensors data (for OG & DATMO) & Avoid false detections on the road surface*







- ***Ground estimation :*** *1m x 1m ground node resolution*
  => ground-points in green, obstacles in pink / red
- ***Occupancy grid :*** *Images 0.1m x 0.1m occupancy grid resolution*
  => green for free space, blue occupied, red unknown



❖ Approach under patenting, to be soon published [1]

❖ Model accurate enough to represent rolling roads & Efficient enough for **real-time** performances on embedded devices

❖ The complete system (including CMCDOT) has been implemented on a Nvidia Tegra X1

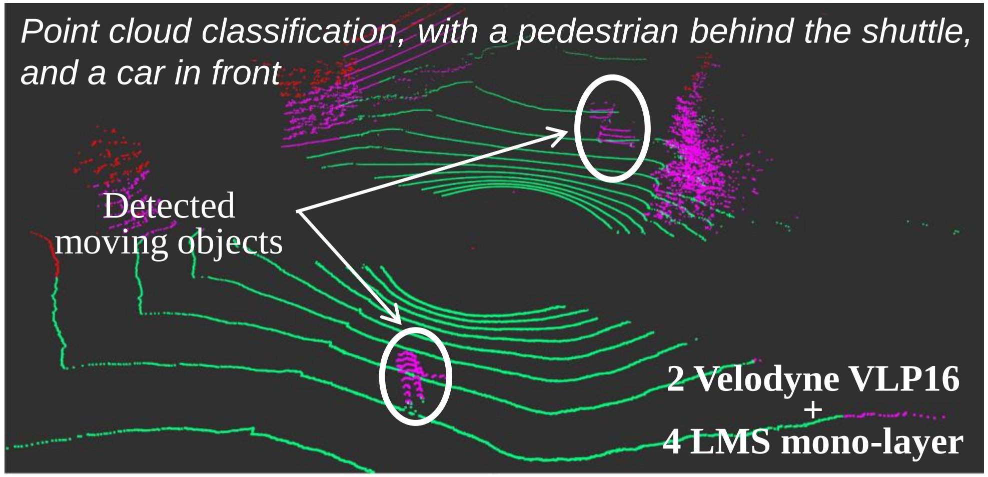
[1] Ground estimation and point cloud segmentation using spatio-temporal conditional random field, Rummelhard et al, IV 2017, Redondo Beach, June 2017

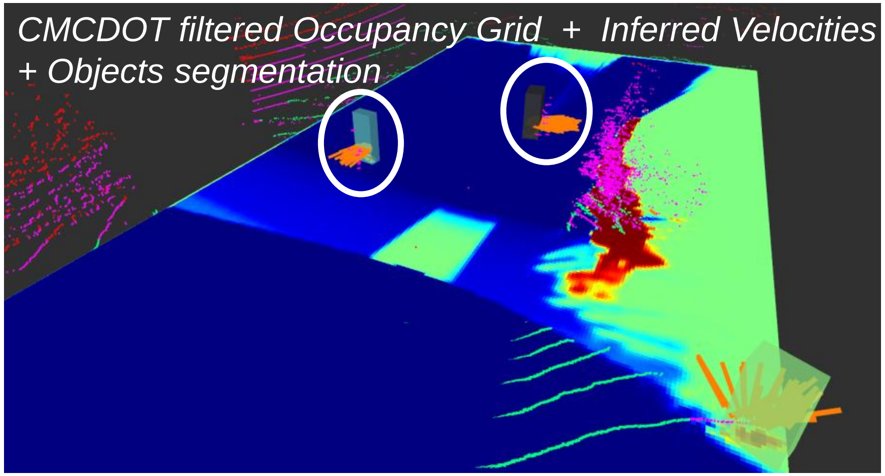
Integration of CMCDOT on a commercial vehicle
(cooperation EasyMile)

- *Founded in 2014, EasyMile is a high-tech startup specialized in providing both software powering autonomous vehicles and the last mile smart mobility solutions*
- *The company (70 employees) is headquartered in Toulouse (France), with offices in Singapore and Denver (USA). It also operates through value added resellers, notably in Japan and the Middle East*

- First tests of integration of the CMCDOT framework system on a commercial automated vehicle
- **The full system is implemented on a Nvidia TX1**, and has directly (and easily) been connected to the shuttle system network (using ROS)

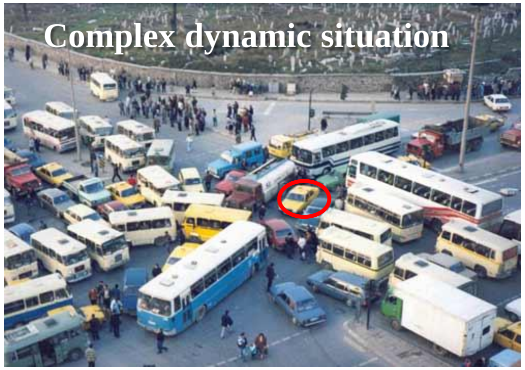
- Sensor data is fused and processed, results are computed and provided in **real-time**
- Further full integration for the commercial product under discussion





Key Technology 2: Risk Assessment & Decision

=> Decision-making for avoiding Pending & Future Collisions



❑ Main challenges

Uncertainty, Partial Knowledge, World changes, ***Human in the loop + Real time***

❑ Approach: Prediction + Risk Assessment + Bayesian Decision-making

- ✓ *Reason about* ***Uncertainty & Contextual Knowledge*** *(using* ***History*** *&* ***Prediction****)*
- ✓ ***Estimate probabilistic <u>Collision Risk</u> at a given time horizon $t+\delta$***
- ✓ ***Make <u>Driving Decisions</u>*** *by taking into account the* ***Predicted behavior*** *of all the observed surrounding traffic participants (cars, cycles, pedestrians …) &* ***Social / Traffic rules***

Underlying Conservative Prediction Capability

=> *Application to Conservative Collision Anticipation*

[Coué & Laugier IJRR 05]

Autonomous Vehicle (Cycab)

Parked Vehicle (occultation)

Pioneer Results (2005)

Thanks to the prediction capability of the BOF technology, the Autonomous Vehicle "anticipates" the behavior of the pedestrian and brakes *(even if the pedestrian is temporarily hidden by the parked vehicle)*

Step 1: Short-term collision risk – *Main features*

=> Grid level & Conservative motion hypotheses (proximity perception)

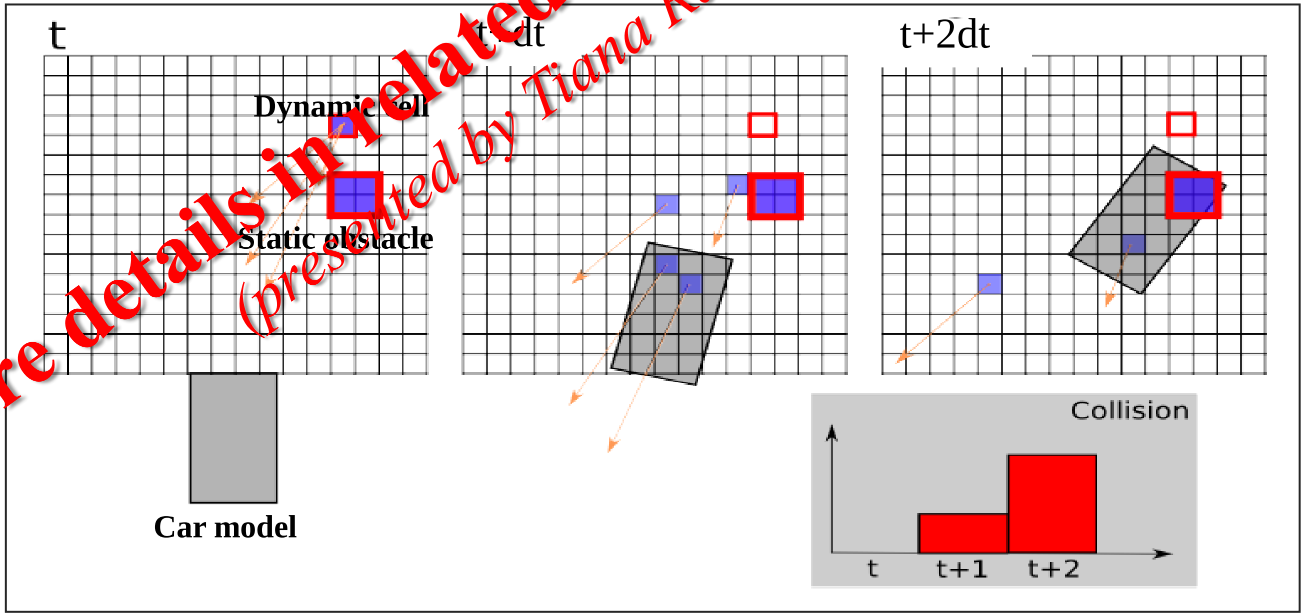
Proximity perception: d <100m and t <5s
δ= 0.5 s => Precrash
δ= 1 s => Collision mitigation
δ > 1.5s => Warning / Emergency Braking

Main Features

- *Detect **"Risky Situations"** a few seconds ahead (3-5s)*
- *Risky situations are **both localized in <u>Space & Time</u>***
  - ⇒ ***Conservative Motion Prediction** in the grid (Particles & Occupancy)*
  - ⇒ ***Collision checking** with **Car model** (shape & velocity) for <u>every future time steps</u> (horizon h)*
- *Resulting information can be used for choosing **Avoidance Maneuvers***

Collision Risk Estimation: *Integration of risk over a time range [t t+δ]*

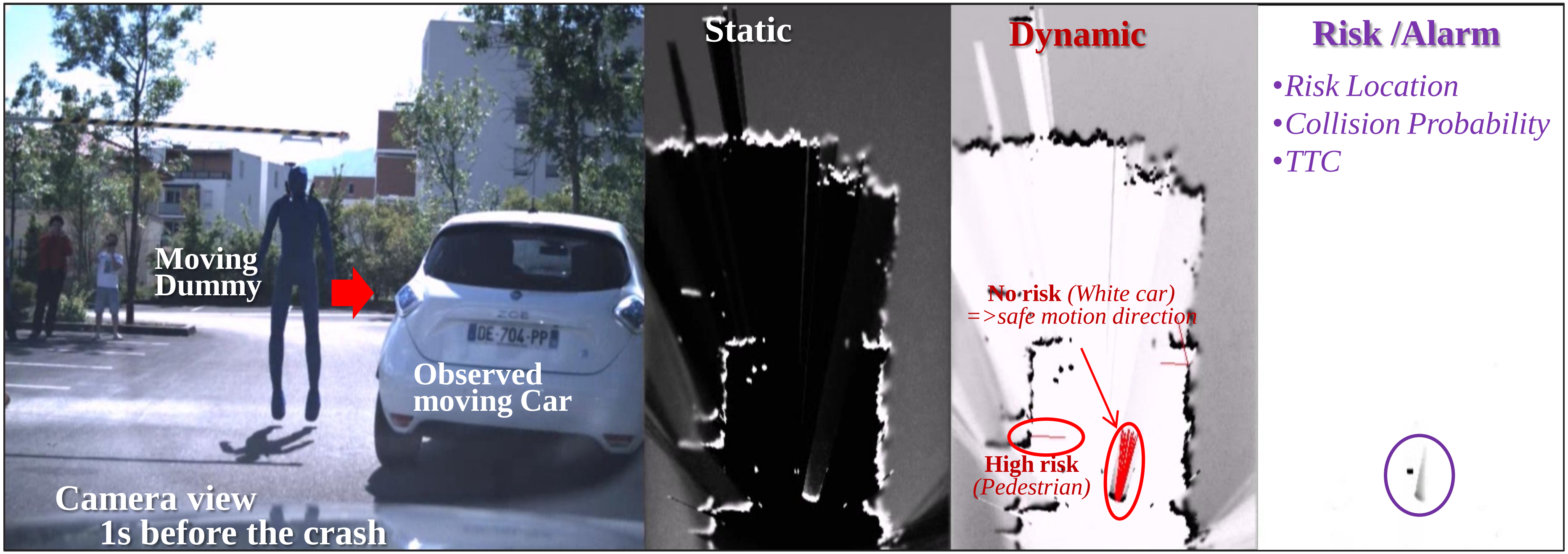
*=> Projecting over time the estimated **Scene changes** (DP-Grid) & **Car Model** (Shape + Motion)*



More details in related Interactive Session
(presented by Tiana Rakotovao)

Short-term collision risk – *System outputs (real-time)*

=> Static & Dynamic grids + Risk assessment



More details in related Interactive Session

(presented by Tiana Rakotovao)

Short-term collision risk – *Experimental results*

⇒ **Detect potential upcoming collisions**
⇒ **Reduce drastically false alarms**

Urban street experiments
=> Almost no false alarm (car, pedestrians …)

Crash scenario on test tracks
=> Almost all collisions predicted before the crash (0.5 – 3 s before)

More details in related Interactive Session

(presented by Tiana Rakotovao)

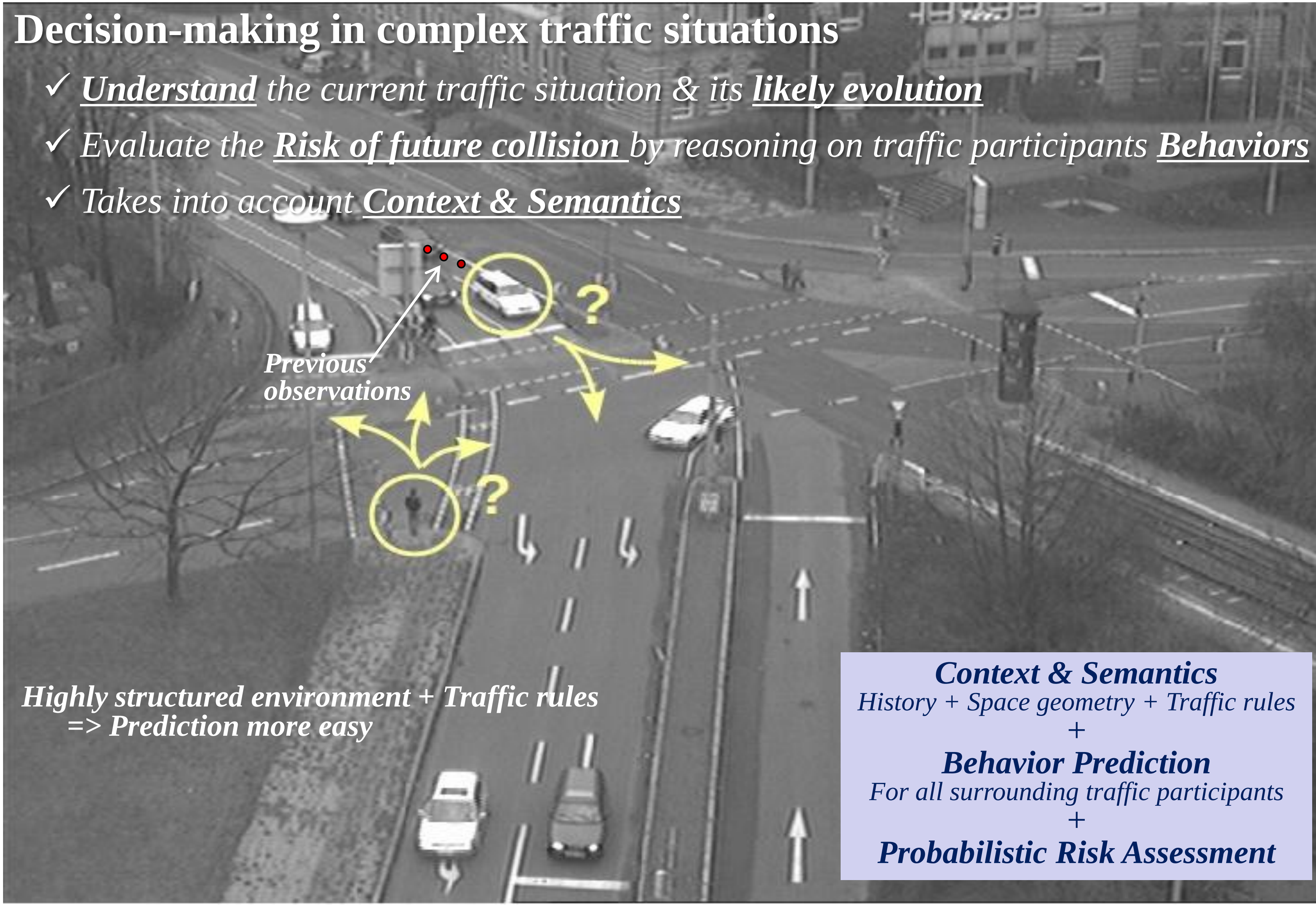
Step 2: Generalized Risk Assessment (Object level)

*=> Increasing time horizon & complexity using **context & semantics***

*=> Key concept: **Behaviors Modeling & Prediction***

Decision-making in complex traffic situations

- ✓ ***Understand*** *the current traffic situation & its* ***likely evolution***
- ✓ *Evaluate the* ***Risk of future collision*** *by reasoning on traffic participants* ***Behaviors***
- ✓ *Takes into account* ***Context & Semantics***



Highly structured environment + Traffic rules
=> Prediction more easy

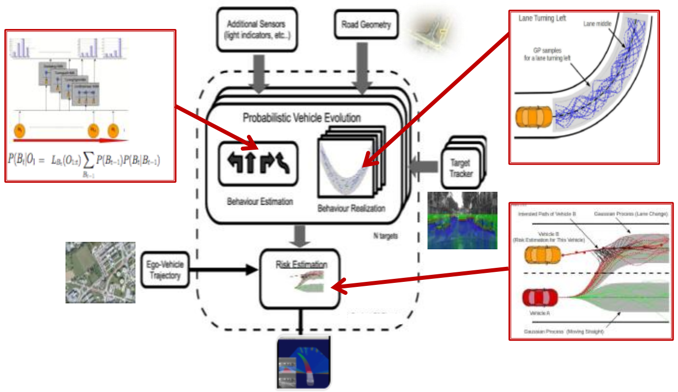
Context & Semantics
History + Space geometry + Traffic rules
+
Behavior Prediction
For all surrounding traffic participants
+
Probabilistic Risk Assessment

Behavior-based Collision risk (Object level)

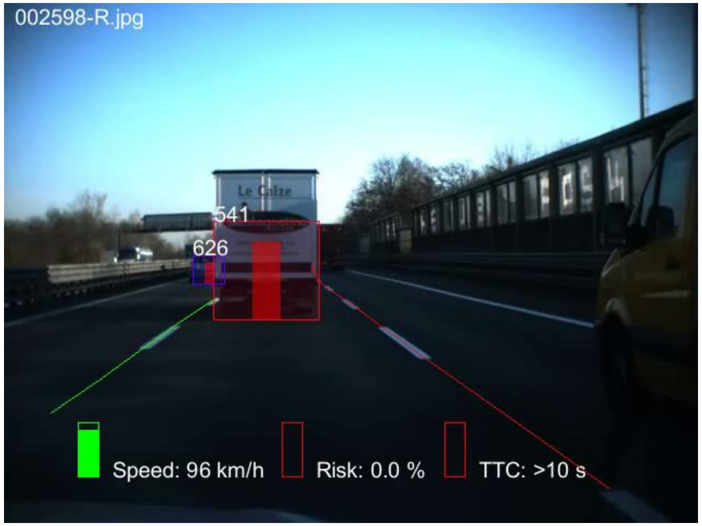
=> Increased time horizon & complexity + Reasoning on Behaviors

❑ Trajectory prediction & Collision Risk

=> Patent Inria -Toyota - Probayes 2010

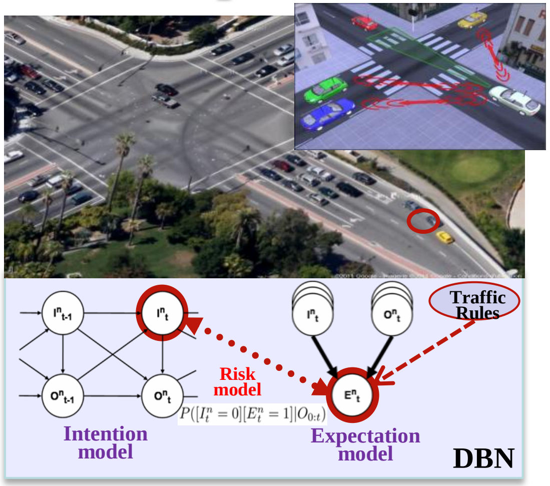


Courtesy Probayes



❑ Intention & Expectation

=> Patents Inria - Renault 2012 & Inria - Berkeley 2013

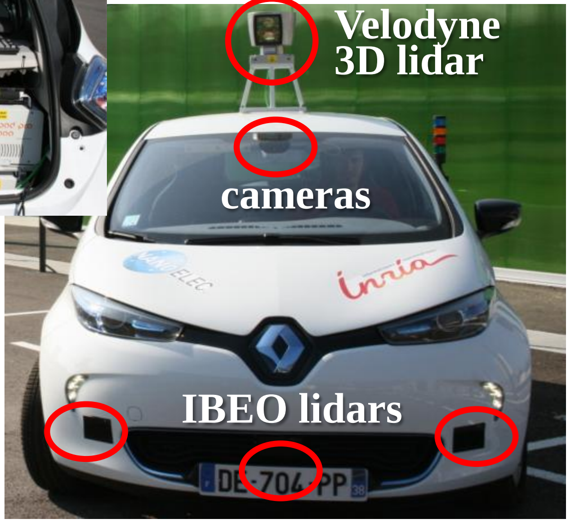


Experimental Vehicles & Connected Perception Units

Toyota Lexus

ROS

Renault Zoé



Connected Perception Unit

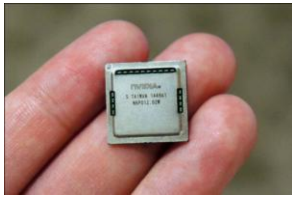
=> Same embedded perception systems than in vehicles

Nvidia GTX Titan X
Generation Maxwell

Nvidia GTX Jetson TK1
Generation Maxwell

Nvidia GTX Jetson TX1
Generation Maxwell

Software / Hardware Integration – *GPU implementation*



- Highly parallelizable framework, **27 kernels** over cells and particles
  => Occupancy, speed estimation, re-sampling, sorting, prediction

- Real-time implementation (20 Hz), optimized using Nvidia profiling tools

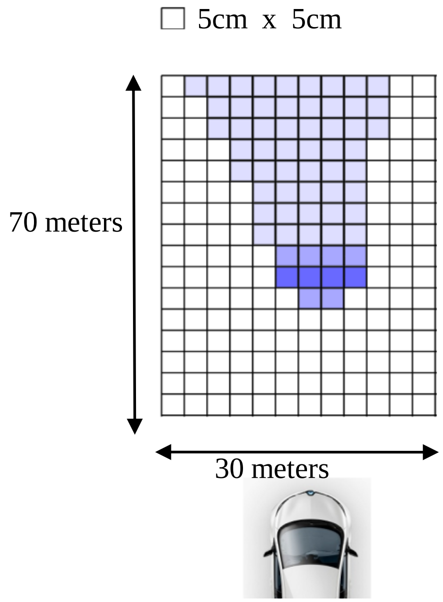
Results:

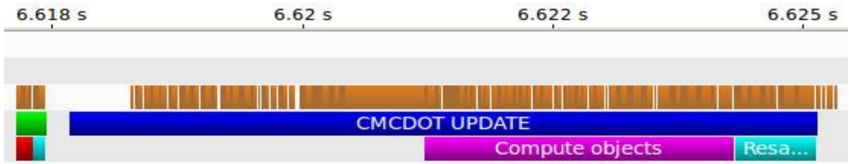
- Configuration with 8 Lidar layers (2x4)

- Grid: 1400 x 600 (840 000 cells) **+** Velocity samples: 65 536

=> Jetson TK1: *Grid Fusion **17ms**, CMCDOT **70ms***

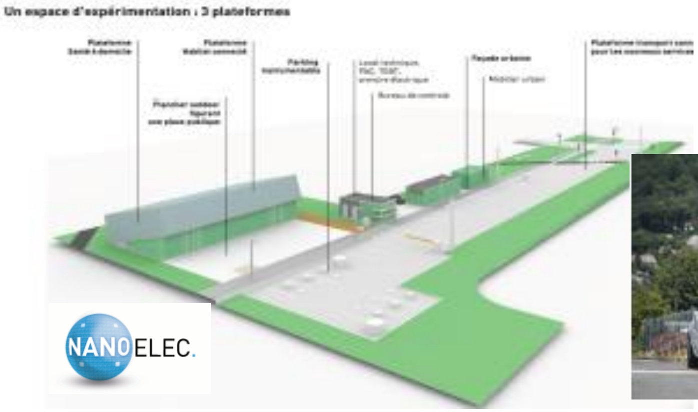
=> Jetson TX1: *Grid Fusion **0.7ms**, CMCDOT **17ms***



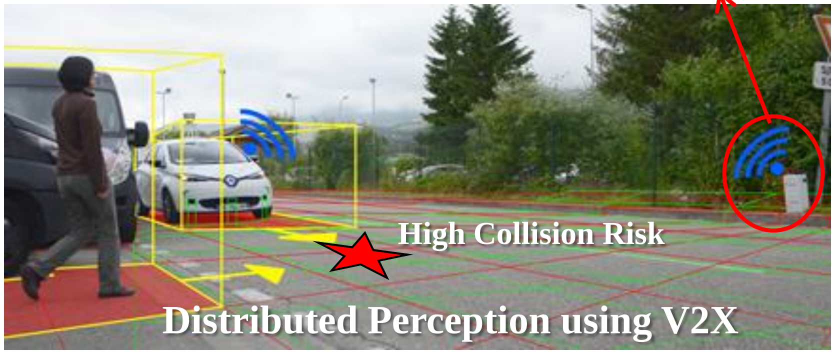


Experimental Areas

- Protected experimental area



Connected
Perception Unit

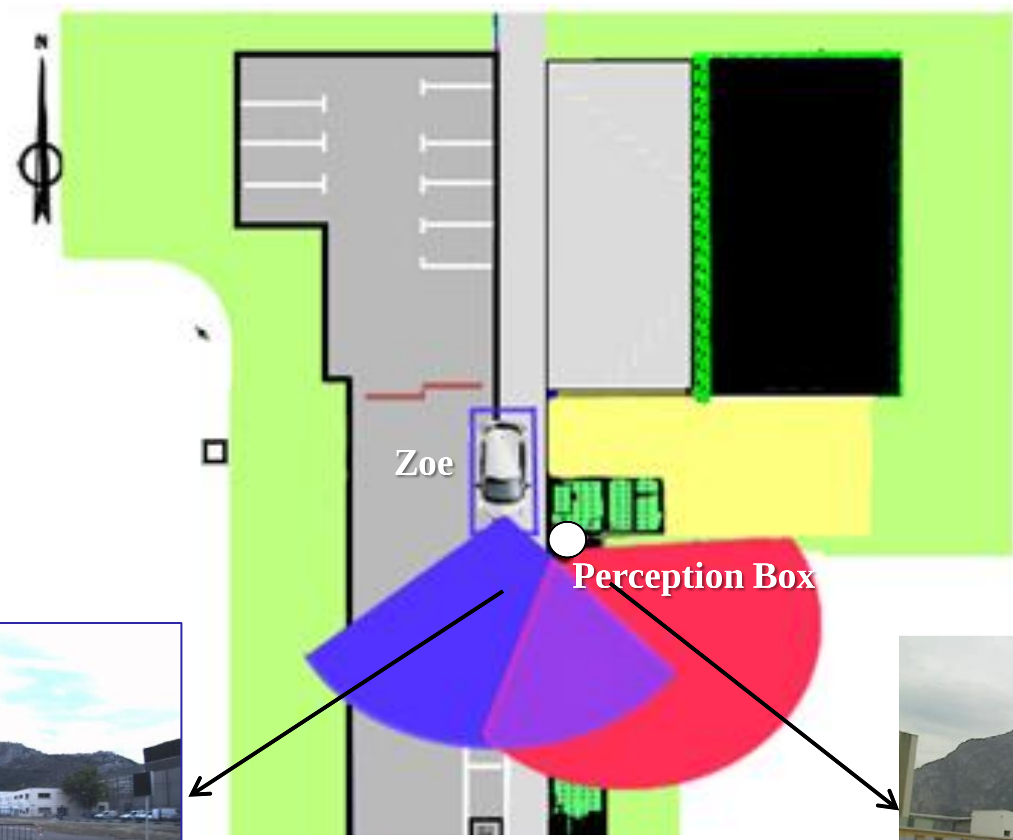


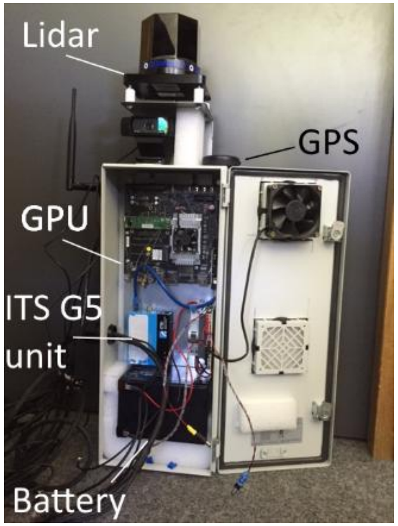
More details in related Interactive Session

(presented by Tiana Rakotovao)

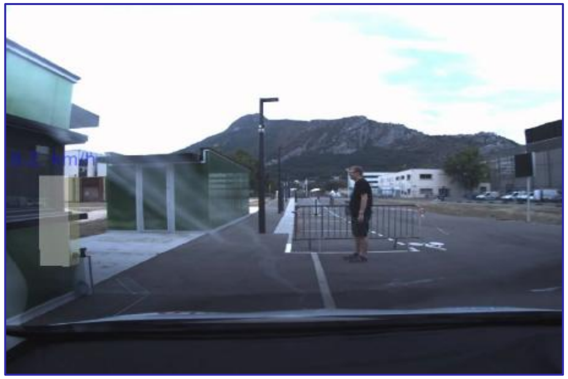
- Open real traffic (Urban & Highway)

V2X: Distributed Perception Experiment

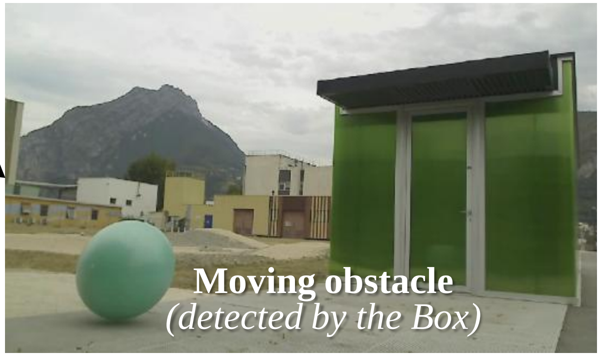




Connected
Perception Unit



Camera Image provided by the
Zoe vehicle



Camera Image provided by the
Perception box

V2X: Data exchange & Synchronization

❑ Data exchange

ROS

ITRI

GPS position + Velocity + Bounding box
(broadcast)

Collision Risk (CMCDOT)
(space & time localization, probability)

ITRI

ITS-G5 (Standard ITS Geonetworking devices)
Basic Transport Protocal IEEE 802.11p

❑ Synchronization

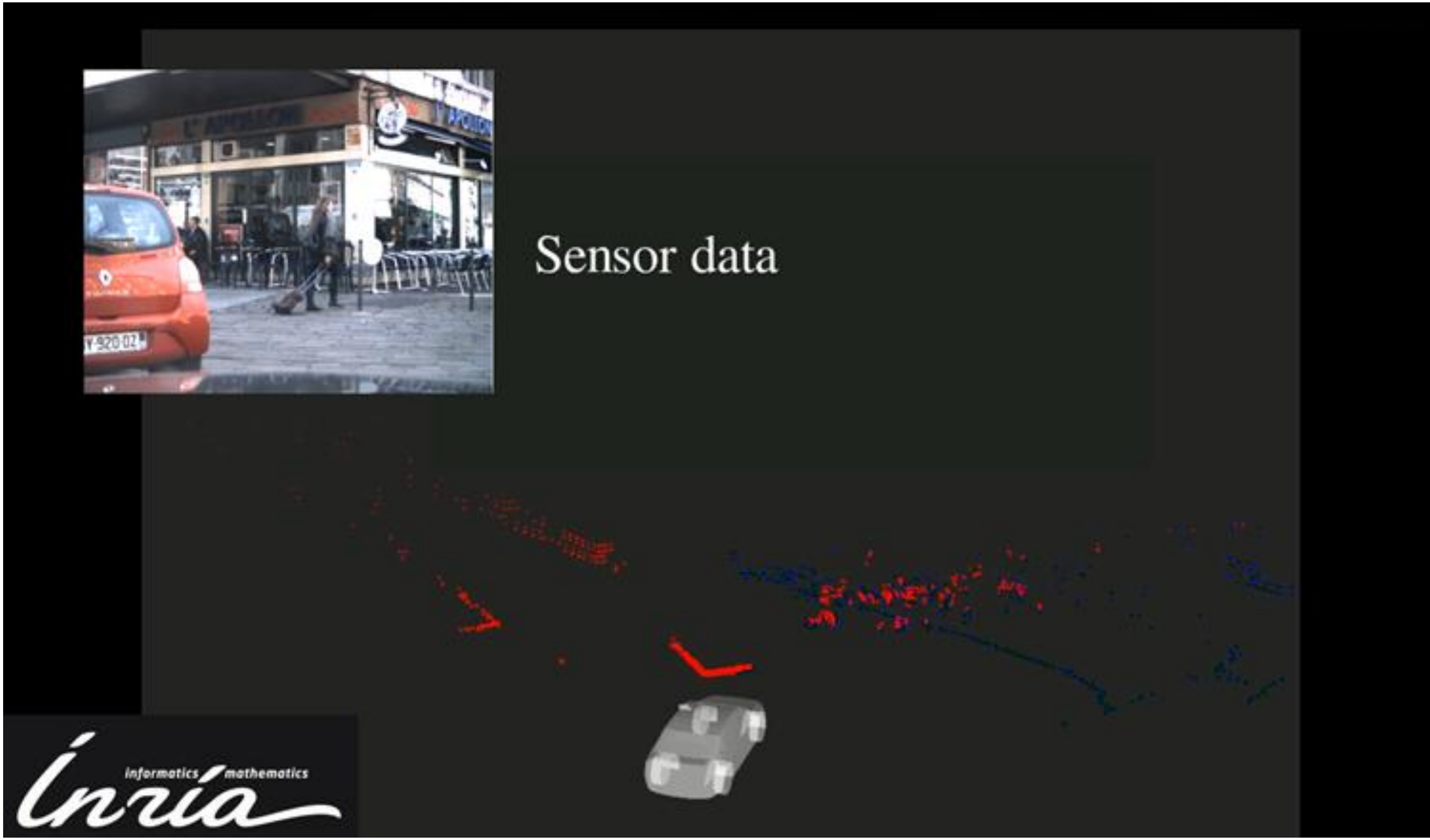
Chrony (**N**etwork **T**ime **P**rotocol)

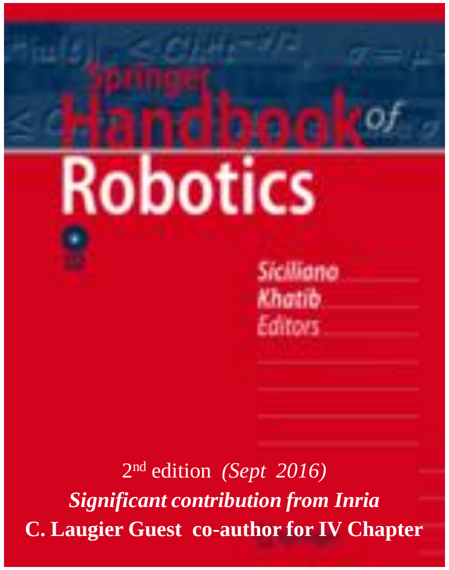
GPS Garmin + PPS Signal (1 pulse per second)

Serial Port

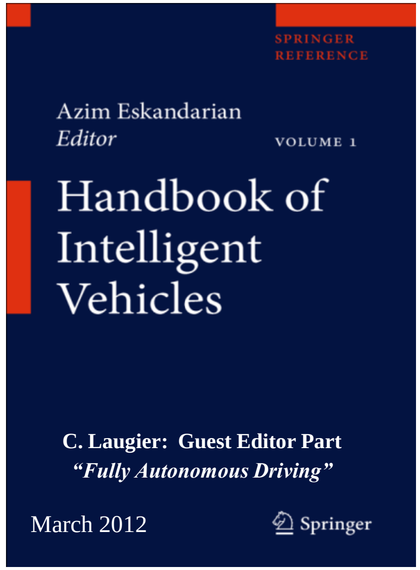
GPIO + UART

CMCDOT – Complete process illustration

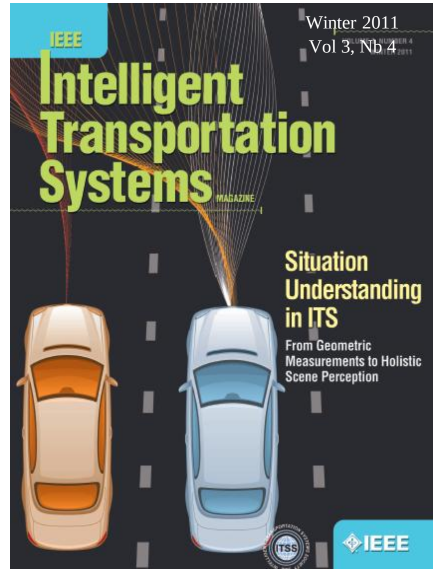




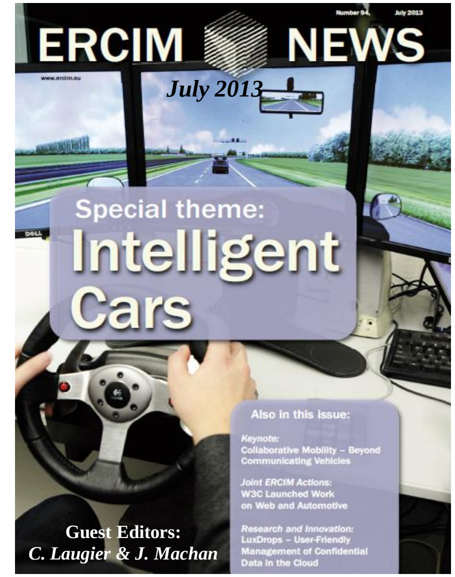
2nd edition *(Sept 2016)*
Significant contribution from Inria
C. Laugier Guest co-author for IV Chapter



C. Laugier: Guest Editor Part
"Fully Autonomous Driving"
March 2012

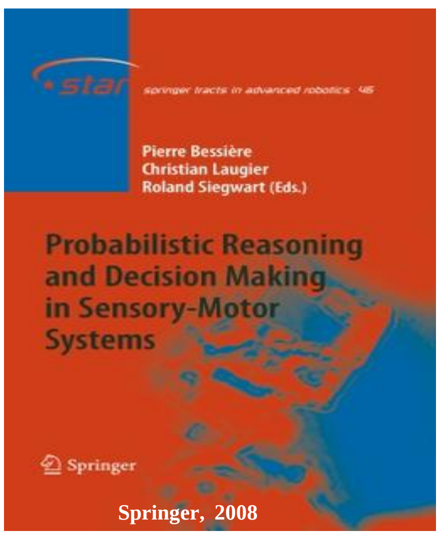


Winter 2011
Vol 3, Nb 4



July 2013
Guest Editors:
C. Laugier & J. Machan

Thank You Any questions ?



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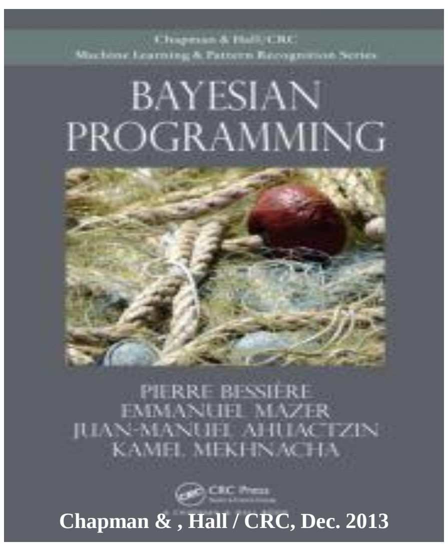

Chapman & , Hall / CRC, Dec. 2013